LARS Print 100372

Definition of Spectrally Separable Classes for Soil Survey Research

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Presented at the Eighth International Symposium on Remote Sensing of Environment, Ann Arbor, Michigan, October 2-6, 1972.

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DEFINITION OF SPECTRALLY SEPARABLE CLASSES FOR SOIL SURVEY RESEARCH

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ABSTRACT

Spectral classes defined by a Euclidean distance criterion have shown similarity to soil classes as mapped by the National Cooperative Soil Survey (local, state, and federal governments cooperating). However, two problems have occurred in past studies:

1) The number of spectral classes defined by the researcher is arbitrary.
2) Spectral properties of nonvegetated soils are modified by rainfall, cultivation, and other factors not directly related to the classes of interest for soil survey purposes.

This research outlines a procedure for defining spectral classes such that the differences between classes can be quantified. It also facilitates determination of a number of classes such that the classes are spectrally discriminable. This is accomplished by partitioning the data into many classes and then combining similar spectral classes on the basis of appropriate criteria.

Multispectral data were collected over a 12-mile flightline in White County, Indiana, in connection with the 1971 Corn Blight Watch Experiment. Data were collected in May by the University of Michigan airborne scanning spectrometer at an altitude of 5000 feet. Spectral maps resulting from the analysis were compared to existing soil surveys of the National Cooperative Soil Survey.

This method should help determine the extent to which spectral properties of soil surfaces can be associated with morphologic and topographic differences of interest to soil surveyors engaged in operational soil mapping.

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1. INTRODUCTION

Several researchers have shown that the spectral properties of nonvegetated soils correlate with other physical and chemical soil properties of interest (1, 2, 4). It has also been shown that spectral classes of soils, as mapped using computer-implemented pattern recognition techniques, correlate with National Cooperative Soil Survey mapping units to some degree (5). However, it is also known that surface conditions can affect spectral properties of soils as measured by an airborne multispectral scanner, and that these effects can sometimes mask the effects of interest to soil surveyors. It is also known that if there were a 1:1 correspondence between soil classes as mapped by the National Cooperative Soil Survey and the spectral classes as mapped using remote sensing that this would be extremely valuable information.

2. OBJECTIVES

The objectives of this research were to 1) find spectral classes in the data which could be discriminated; 2) define a repeatable method for obtaining these discriminable spectral classes; 3) compare the resulting spectral classes with the National Cooperative Soil Survey mapping units; 4) determine the extent to which the National Cooperative Soil Survey mapping units could be discriminated spectrally.

3. MATERIALS

The study area was a 12-mile flightline in White County, Indiana (Segment 208 of the 1971 Corn Blight Watch Experiment). The soils are of glacial origin being composed largely of glacial till and outwash. Windblown silts occur in parts of the study area. The soils have a range in surface textures from silty clay loam to sandy loam. The soils in this study area are described briefly in Table 1.

Multispectral data were collected on May 17, 1971 at 1:29 p.m. by the University of Michigan aircraft at an altitude of 5,000 feet, with a ground heading of 180°.

4. PROCEDURES

For the analysis, the flightline was divided longitudnally into two halves, east and west, to minimize the effects of look angle and sun angle. Each half was analyzed separately. Exhaustive samples which represented areas of bare soil were selected from multispectral imagery. These samples were pooled, and a cluster analysis was conducted using the LARSYS program NSCLAS (8). Fifteen classes were specified in the cluster analysis in order to be sure to define at least as many spectral classes as there were soil mapping units. It was anticipated that from six to ten soil mapping units might exist in such an area in this length of flightline. Seven wavelength bands in the visible region (0.40-0.70 μm) were used throughout the analysis.

A set of test fields was selected using a systematic random procedure. Each test field was assigned to the soil survey mapping unit which it represented. This was the first stage in the analysis at which ground information regarding mapping units was employed. Prior to this stage only spectral information was used in the definition of classes.

After having defined the spectral classes using the clustering program, the entire area was classified using the cluster classes as the basis for training. This classification procedure utilized a maximum-likelihood algorithm (6).

The distribution of the soil mapping units (represented by the test fields) into the 15 spectral classes was examined. Mapping units were combined if they were not spectrally distinct, and the distribution of the test field data into grouped spectral categories was examined. Grouping was accomplished using Figure 1, as described in the following paragraphs, and was based on an average quotient of less than 1.0 within groups.

Cluster classes were combined into groups by first combining those classes which were most similar, based on the quotient value. In the example (Figure 1), this was classes 14 and 15 which had a quotient of 0.50. Then the next most similar class, 10 and 11, (quotient = 0.56) were combined. This was followed by combining classes 4 and 5, then 6 and 7, then 12 and 13. etc. At each step the possibility of a single class combining with an existing group of two or more classes was checked. Likewise, as the procedure continued, groups were combined with other groups. A consistent rule was employed at every step, which may be stated as follows. Classes or groups were combined to yield the smallest quotient or average quotient for all pairwise comparisons within the new group. This procedure is described and discussed more fully by other researchers (3, 7).

Figure 2 shows the distribution of the test field data for one-half of the flightline into the 7 groups which were derived from the information in Figure 1.

On the left is the soil series which was mapped by the soil survey. Prior to combining 15 classes into 7 classes, Dana and Parr were not found to be spectrally

discriminable; so they were grouped in this table. The table shows the number of points (resolution elements) which occurred in each of the new spectral groups which were defined. The Miami soil had a rather small sample, only 8 points, but these were all classified into Group 1, the brightest group. The Plainfield soil had 40 points, all of which were classified into spectral Group 1, also. The Dana and Parr occurred primarily in spectral groups 2 and 3. This means that Dana and Parr soils are slightly darker in tone than the Miami and Plainfield soils and that this fact was detected by the scanner and the analysis procedure.

The Chalmers soil occurred almost entirely in cluster group 7, the darkest spectral group. It is possible to reduce this table still further by grouping together Miami and Plainfield samples, since these two were not found to be spectrally discriminable from one another, and considering groups 2 and 3 as being related to the Dana and Parr soils.

Figure 3 shows the recognition of soil types based on these criteria. By this grouping, the three groups of soils were recognized 91.6% correct on the average.

5. CONCLUSIONS

Three groupings of soil mapping units were differentiated spectrally by these procedures. Five different mapping units had been delineated by the soil survey in this area. Clusters were not sharply defined in the data. This is reasonable when considering the continuous nature of soils and their occurrence on the landscape. Soils often grade from one into another on the landscape rather than having sharply defined boundaries between them. Some soil mapping units were quite similar to one another and had a rather large amount of spectral variability within a mapping unit. From this analysis, we conclude that one to one correspondence between soil survey mapping units and discriminable spectral classes is unlikely for glacial soils of Western Indiana.

The three groups which were separated in this study correspond to some extent to management groups. The Chalmers soil occurs in depressions and is usually tile drained to make it agriculturally productive. It also has limitations for urban and other purposes.

Dana and Parr can be cultivated without tile drainage, and are often more productive soils than Miami and Plainfield.

Finding Dana and Parr soils spectrally similar was not an unlikely result. Apparent nondiscriminability of Miami and Plainfield, however, was not anticipated since these two soils are quite different in terms of surface texture and other properties. It seems possible that future investigations may explain this phenomenon, or at least achieve greater spectral separability for such soils.

6. REFERENCES

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TABLE I. SOILS OF THE STUDY AREA.

Soil Series and Surface Texture	Typical Surface Color (Munsell)	Natural Drainage
Plainfield sand	10 YR 4/2	well drained
Miami silt loam	10 YR 4/2	well drained
Parr silt loam	10 YR 3/2	well drained
Dana silt loam	10 YR 3/2	moderately well drained
Chalmers silty clay loam	10 YR 3/1	very poorly drained

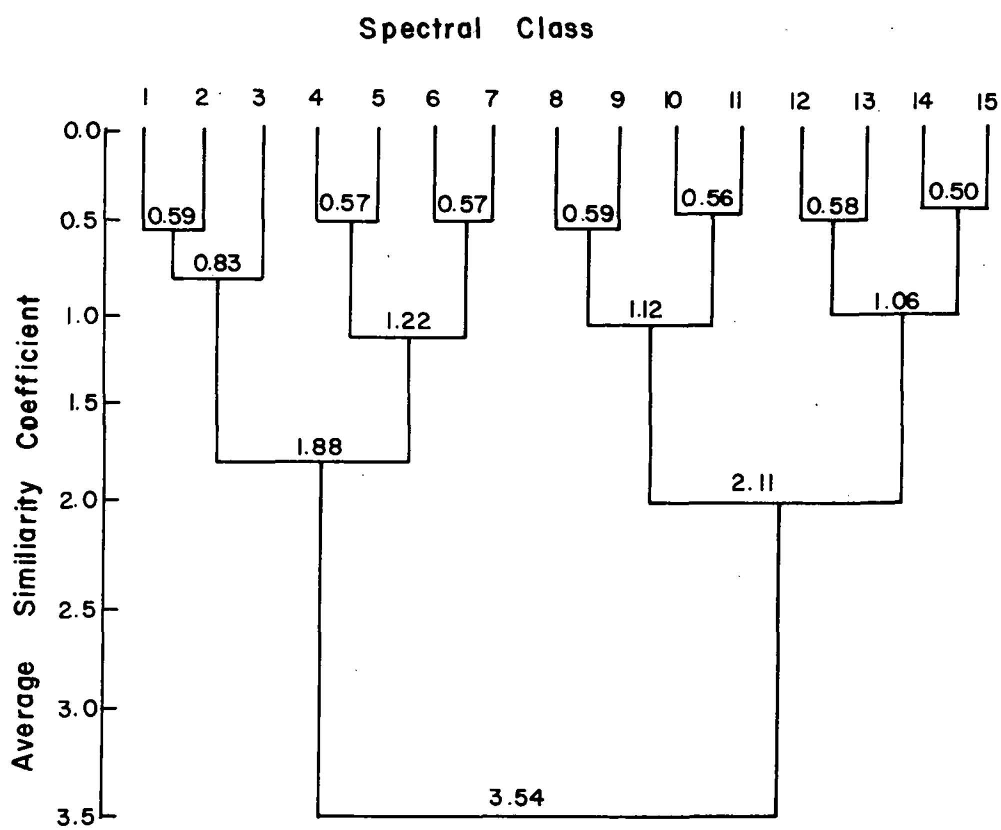

FIGURE 1. DIAGRAM SHOWING GROUPING OF 15 CLUSTER CLASSES BASED ON SIMILARITY COEFFICIENT.

Soil Series	Spectral Group 1	2	3	4	5	6	7
Miami	8	0	0	0	0	0	0
Plainfield	40	0	0	0	0	0	0
Dana-Parr	16	100	92	4	0	0	0
Chalmers	0	12	16	0	0	32	304

FIGURE 2. DISTRIBUTION OF TEST SAMPLE POINTS INTO SEVEN SPECTRAL GROUPS.

Soil Series	% Correct
Plainfield, Miami	100.0 %
Dana, Parr	88.6
Chalmers	92.2
Overall	91.6 %

FIGURE 3. PERCENT CORRECT RECOGNITION OF FIVE SOIL TYPES WHEN COMBINED INTO THREE GROUPS.